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# The role of simulation as a method for sales forecasting – A systematic literature review

Tobias Klima[1,*], Markus Rabe[1] and Michael Toth[2]

[1]TU Dortmund University / IT in Production and Logistics, Leonhard-Euler-Str. 5, Dortmund, 44227, Germany
[2]Bochum University of Applied Sciences / Production Management and Logistics, Am Hochschulcampus 1, Bochum, 44801, Germany

*Corresponding author. Email address: tobias.klima@tu-dortmund.de

## Abstract

This paper aims to analyze the role of simulation as a method for sales forecasting through a systematic literature review using a methodology based on existing research procedures. Before starting the research, the scope of the study was determined, the research questions defined, and the search parameters determined. The selected databases were searched and the articles found were subjected to a selection process. The articles that were classified as relevant were analyzed further. The study aimed to find out how widespread the use of simulation as a sales forecasting method already is, whether there is a growing interest, whether and how simulation is used in conjunction with other methods and also tested on practical examples, and what types of simulation are used. The analysis shows that two simulation methods are dominant in this field, in which industries they are most common, and that they are mostly used in combination with other forecasting methods. It also allows assumptions to be made as to whether the use of simulation in this area will increase.

**Keywords:** systematic literature review; simulation; sales forecasting

## 1. Introduction

The importance of sales forecasting has significantly grown in today's business world. Accurate predictions of future sales are crucial for optimizing inventory, planning production capacity, and effectively allocating resources. Companies rely on precise sales forecasts to minimize costs while ensuring customer satisfaction. This is shown by several studies on this topic (Ostrow, 2016; Fatemi, 2018). Forbes magazine, for example, writes "Companies boasting accurate sales forecasts are 10 % more likely to grow their revenue year-over-year" (Fatemi, 2018).

If the company does not want to rely on the estimate of an expert, statistical methods such as using moving averages to predict sales are easy to apply. Although these methods provide a solid basis, they quickly reach their limits or lose their accuracy in more complex fields of application. In recent years, the use of machine learning has become increasingly important to create more accurate and dynamic sales forecasts. With the help of machine learning, companies can utilize a wealth of data sources to create forecasts that can adapt to changing market conditions. As a result, the reviews of sales forecasts on this topic also focus on these two forecasting methods (Junior et al., 2023; Eglite and Birzniece, 2022).

In addition to these methods, it is also possible to use simulation as a method for various forecasts. However, there is no review published that analyzed this area. Furthermore, the concept of coupling simulation with

other methods has repeatedly proven to be a performance gain and a success factor (Better et al., 2007; Kiefer et al., 2023). The ability of simulation to incorporate important assumptions into the model alongside the company's existing data appears to be a reasonable approach. Therefore, it is worth investigating the extent to which it can be used in conjunction with sales forecasts. In this article, it is analyzed whether there is a trend over time that indicates an increase or decrease in the use of simulation for sales forecasting, which simulation methods are used, whether these are combined with other methods (e.g., statistical methods), and which sector is the focus in this area.

The following sections are organized as follows: In Section 2, the scope of the investigation is defined and an overview of the general approach to conducting the systematic literature analysis is provided. Section 3 describes in detail the systematic literature review carried out for the area described in Section 2 and provides an extract of the list of all relevant sources identified. This section offers insights into the existing body of knowledge within the scope of the study. Section 4 is dedicated to the in-depth analysis of research findings and their critical evaluation of the research gap introduced in Section 1. This section is vital for understanding the implications of the presented research and its contributions to the field. Finally, Section 5 summarizes the findings and gives an outlook on potential future research areas and developments in this subject.

## 2. Methodology and scope of study

This section is dedicated to the general procedures of systematic literature analyses and defines the scope of the investigation. In Section 2.1, an overview of the general methodology of a systematic literature analysis is provided. The key steps involved in conducting a systematic review are elucidated, including the definition of the review scope, the definition of the search strategy and parameters, the identification and selection of relevant papers, the forward and backward search, and the analysis of relevant papers. These fundamental insights will assist readers in comprehending the systematic approach employed in the study.

The section on the basic terminology of the research area introduces the fundamental terms and definitions for the research domain. The crucial search terms, keywords, and their synonyms or closely related terms utilized during the literature search are defined. This clarification is pivotal to ensure consistency and precision in the information retrieval process.

Section 2.3 delineates the specific search platforms and databases that were employed to gather relevant literature for the analysis. The reasons for selecting these platforms are described and an explanation of how they contribute to the comprehensiveness of the investigation is given. Furthermore, this paper also provides insights into the search strategies and filters employed to collect pertinent publications.

Each of these sections contributes to a comprehensive understanding of the methodology applied in the systematic literature analysis, the platforms where the literature was collected, and the specific terminology used for identifying and retrieving relevant publications.

### 2.1. General methodology of the literature analysis

The general form of a systematic literature research (SLR) consists of the following steps (Durach et al., 2017):

1. Definition of the research question (RQ)
2. Specification of the desired characteristics and the initial study requirements
3. Collection of a set of potentially relevant publications
4. Selection of appropriate literature
5. Synthesis of publications
5. Communication of the results

It is important to ensure a detailed, transparent, relevant, and replicable SLR (Tranfield et al., 2003; Wetzstein et al., 2016). To achieve this, the process is based on the four steps of Jane Webster and Richard T. Watson (2002) and Cato (2016). These are (1) definition of the search strategy and parameters, (2) identification and selection of relevant papers, (3) forward and backward search, and (4) analysis of relevant papers (Cato, 2016; Webster and Watson, 2002). Vom Brocke et al. (2009) defined these steps, but added the "definition of review scope" beforehand. This step is also taken up by Soni and Kodali (2011).

This results in the following five work steps, which are described in detail in the above-mentioned literature:

1. definition of review scope
2. definition of search strategy and parameters
3. identification and selection of relevant papers
4. forward and backward search
5. analysis of relevant papers

These five steps are explained in Sections 2 and 3.

### 2.2. Definition of review scope

The first step is the definition of the review scope. A specific research objective is the basis for a literature review (Mayring, 2014). The research objective of this literature review is to provide an overview of simulation as a method for sales forecasting. The following *research* questions are posed to analyze how simulation can be utilized to create or enhance sales forecasts and how widespread the use of this method

currently is:

1. How many publications deal with simulation as a sales forecasting method?
2. Can simulation be expected to become more widespread?
3. What types of simulation are used?
4. Are there only theoretical concepts or application examples?
5. Which area do the application examples come from?
6. Is simulation used in combination with other methods?
7. If the simulation was used in combination with other methods, for what purpose was the simulation used?
8. Which research gap is described in the relevant literature?

To analyze these questions, it is first necessary to define the various terms used. Since the aim of the paper is to provide an overview of simulation as a method for sales forecasting, the three terms simulation, sales, and forecasting are defined. First, simulation is defined as the "reproduction of a system with its dynamic processes in an experimental model to arrive at findings that can be transferred to reality. [...]" (VDI, 2014, p.3). The word "sales" in the context of forecasting is defined as the "labelling of the quantities of goods sold" (Gutenberg, 1963, p.1). There is no generally accepted definition of forecasting in the literature (Döhrn, 2014). The following definition was derived from Döhrn (2014, p. 6): "forecasting is a scientifically based prediction of future events, conditions, or developments".

To also determine whether simulation is used in conjunction with other methods, the two methods mentioned in Section 1 are described in more detail. Machine Learning (ML) refers to a computer program that autonomously learns from experience and aims to optimize its performance towards a predefined goal (Mitchell, 1997). An example of ML is an artificial neural network (Mertens and Rässler, 2012). Simple statistical methods (SM) are purely mathematical and statistical techniques, such as moving averages (Mertens and Rässler, 2012).

Once the terminology had been defined, Vom Brocke et al. (2009) recommended the use of Cooper's taxonomy to clearly define the scope of a literature analysis (Cooper, 1988). This taxonomy has been adapted to the goals of this study (Table 1).

1) The *focus* is determined taking into account the research questions posed. The focus of the SLR is on the methods used in the publication (simulation, ML, SM), but application examples are also relevant for Question 5. Theoretical concepts are also considered.

2) The *goal* of this study is to provide a general statement for the area under consideration by creating a research overview from several specific examples.

3) In order to be able to analyze the research question of the increase or decrease in publications in the research area, it was decided to *organize* the data in chronological order by publication date.

4) The study is carried out from the specific *perspective* that simulation can be used as a method in sales forecasting and the focus of the SLR is on simulation.

5) The answer to the research gap is aimed at a specific *audience* and is, therefore, directed at specialized scholars.

6) As the paper aims to *cover* and analyze all relevant scholarly contributions, it constitutes an exhaustive analysis. In the next step, the most relevant databases for the search are selected, which can also be referred to as a form of selection.

**Table 1.** Taxonomy of literature reviews following Cooper (1988).

| Characteristi | Categories | | | |
|---|---|---|---|---|
| 1) focus | research outcomes | research methods | theories | applications |
| 2) goal | integration | criticism | | central issues |
| 3) organi-zation | historical | conceptual | | methodical |
| 4) perspective | neutral representation | | espousal of position | |
| 5) audience | specialized scholars | general scholars | practitioners/ politicians | general public |
| 6) coverage | exhaustive | exhaustive and selective | representative | central / pivotal |

## 2.3. Definition of search strategy and parameters

The second step of the process defines which databases are searched for the relevant literature and what requirements have to be respected. Requirements such as the length or date of the articles must be defined. The most important requirement is the set of search terms that are used to identify the articles (Cato, 2016; Webster and Watson, 2002).

The search terms selected for this literature review are listed in Table 2. For the selection of search terms, the terms already known from Section 2.2 were used and supplemented by closely related terms to cover as many articles as possible in the area of investigation.

All search terms were combined with an OR-operator for the query in the database. The databases Scopus, IEEE Xplore, ACM Digital Library, and AIS Library were selected to search for relevant articles (Table 2). In order to ensure broad coverage without overly narrowing the focus initially, all publications with the search terms in the title, summary, or keywords were included. Scopus offers a direct option for this. For all other databases, this was done manually. The publication date was not restricted and

refers to all publications published up to 13 February 2024.

**Table 2.** Search databases and terms.

| Databases | Search terms |
|---|---|
| Scopus | 1. "simulation" |
| | AND |
| IEEE Xplore | 2. "approach" OR "method" OR "technique" |
| | AND |
| ACM Digital Library | 3. "sales" |
| | AND |
| AIS Library | 4. "forecasting" |
| | AND |
| | 5. "model" |

## 3. Systematic literature research

In this section, the third step for the SLR is carried out. First, the literature search with the defined search parameters is conducted (Section 3.1). All double entries are removed. This is followed by three selection stages. In the first stage, the papers that did not fit by their title or lead to access problems were sorted out. For example, the title "A study of applying artificial neural network and genetic algorithm in sales forecasting model" was sorted out due to a warning about a security risk when accessing it. In the second stage, the abstract was read and articles that do not fit in terms of content are sorted out. In the third stage, the remaining articles were read in detail, those that did not fit sorted out again and those that fit sorted according to the research questions and "organization", as defined in Table 1 (Section 3.3.). After the keyword search, the articles classified as relevant were used for the backward search (Section 3.2.). Backward search means checking the references of these articles. This is followed by a forward search, which checks who has cited the articles classified as relevant (Levy and J. Ellis, 2006; Cato, 2016; Webster and Watson, 2002).

### 3.1. Identification and selection of relevant papers

The search across all four databases with the search terms specified in Table 2 resulted in 532 hits. All search terms were truncated at their extension to avoid having to differentiate between nouns, verbs, or adjectives (e.g., "forecasting" was searched for in the databases with "forecast*"). 40 articles have been removed due to double and 11 due to triple entries. In the first stage, 183 articles were removed. Of the remaining 298 articles, further 127 were removed on closer analysis of the abstract. In the third stage, 55 more were removed on closer reading. The remaining 116 articles have been sorted thematically. The sorting was based on the areas covered in the respective article and how intensively they were considered. If the article deals with the area as a core topic, the topic was colored dark grey and otherwise light grey. The subject areas are "Simulation", "Forecasting" and "Sales", whereby a distinction was made in the case of sales as to whether the seller side (referred to here as "Sales") or the buyer side ("Customer“) was considered.

Additionally, the strength of the connection between the subject areas was evaluated. If the connection of one subject area to another one was just mentioned, a dashed arrow was used. If both topics were dealt with together, a solid arrow was used. Since the focus of the paper is on simulation as sales forecasting method, the prerequisite for being classified as relevant is that simulation, forecasting, and one of the other two categories must be at least classified in light grey and be connected to both of the other topics. Under these conditions, 116 articles were classified as relevant; all other 416 articles were sorted out in one of the stages and were not further considered for this work.

**Table 3.** Example for the selection of relevant papers.

| Article | Sales | Simulation | Forecasting | Customer |
|---|---|---|---|---|
| Yan, 2016 | | | | |
| Konstantin et al., 2014 | | | | |
| Aksyonov et al., 2013 | | | | |
| Bruzzone et al., 2009 | | | | |
| Stahmer and Schwaiger, 2004 | | | | |
| Munoz, 2003 | | | | |

### 3.2. Forward and backward search

The 116 articles classified as relevant were used for the backward search. Due to citations within one of these articles or based on their title in the sources, additional 79 articles were considered. As the title had already been read and was mentioned in an article that had already been categorized as relevant, it was possible to start at stage three, if access was possible. 20 of the 79 articles were classified as relevant.

The forward search revealed that further 40 articles could be considered, 16 of which were included in the table of relevant articles. It should also be mentioned that a forward and backward search was also carried out for the newly found relevant articles listed in this section. These are already included in the numbers mentioned.

### 3.3. Analysis of relevant papers

Before presenting the result of the literature search, the research is summarized in Figure 1 for a better overview. The remaining 152 articles were included in a table. To be able to answer all the research questions

from Section 2.2, the articles were analyzed and classified by these in a second run. Four different categories were defined and the articles were sorted as indicated in Table 1 (Webster and Watson, 2002). An exemplary section is shown in Table 4.

It was checked whether other forecasting methods were used in combination with simulation and whether all methods were applied or if they were only presented as a theoretical concept. Secondly, the simulation method used was analyzed in more detail. It became apparent that there were major differences in the depth of the description of the methods, from just mentioning the word "simulation" to detailed applications. To enable a categorization, the categorization according to Sauerbier and Mildenberger (1999) was adhered and the focus there was placed on the definitions used. Sauerbier and Mildenberger (1999) allow a categorization into deterministic and stochastic simulation. The first category consists of models that are clearly deterministic, in which an attempt is made to describe the system. An example of such a "descriptive system" is the simulation part of a publication for vending machines. Firstly, fuzzy logic and a multi-factorial regression model are used to predict the number of cans dispensed daily by the vending machines. In the second step, a simulation model is used to determine the costs of the forecast if the vending machines are only filled with the required number of cans. The simulation model, therefore, contains all the descriptive terms for the costs of the vending machines (e.g. the cooling energy) (Sakai et al., 1999).

The second category is located between the clear division into deterministic and stochastic and refers to models in which interactions and decisions receive a central role. These "decision models" can be agent-based models that aim to predict the acceptability of biofuels at the petrol station (Kiesling et al., 2010). "Probability models" were categorized in the third category. This is about simulation with random variables, i.e., stochastic methods such as Monte Carlo simulation (MCS) to simulate random trading market data of social consumer goods (Xin and Lu 2022). In the fourth column of Table 4, the question of the specific application was examined and in the last column, the different areas in which the articles were published were considered. Several categories were formed for this purpose: Automotive industry (OEMs, suppliers, spare part manufacturers, dealers, etc.), food industry (supermarkets, beverage markets, farmers, etc.), energy industry (power supply, petrol stations, wind farms, etc.), electronics industry (new technologies but also everyday consumer goods), and fashion industry (clothing but also beauty and grooming). Larger networks of many players were summarized under "Macroeconomics". Generally, valid papers were listed under "General" and all those that did not fit into any of the industries mentioned were sorted under "Other". In addition, there were a few papers in which the industry was not named.

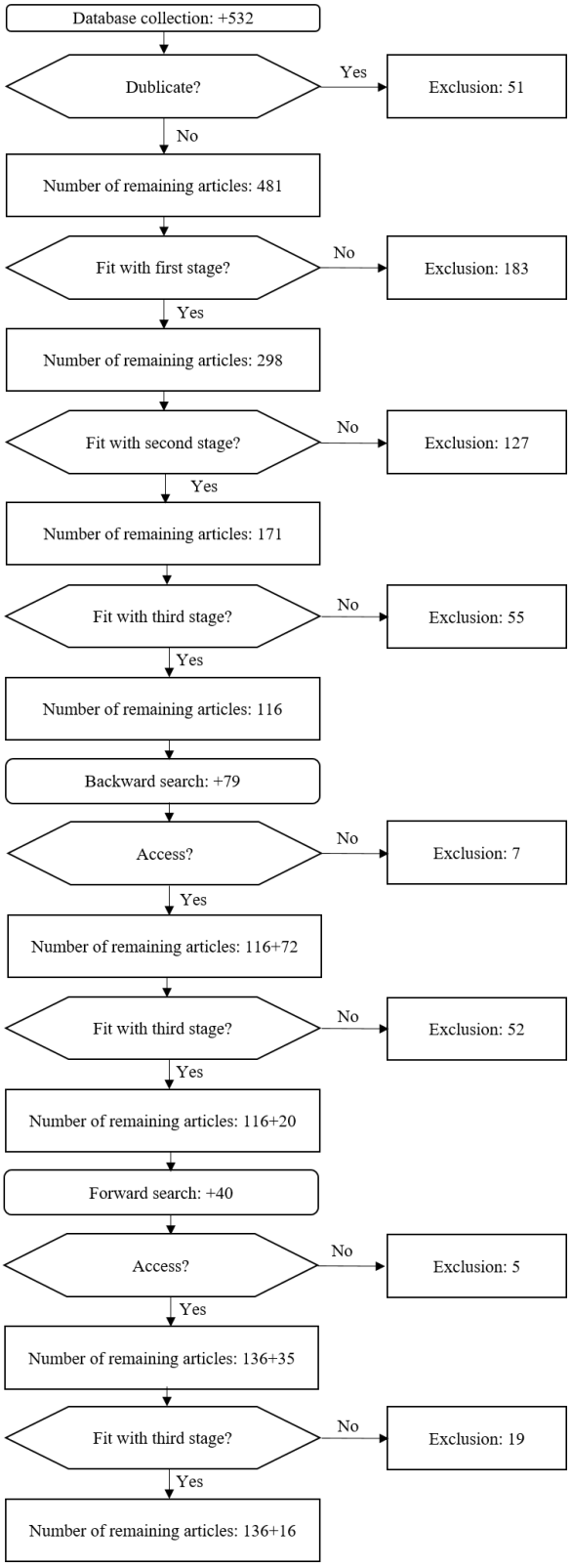


**Figure 1.** Summary of the literature research (according to Moher et al., 2009).

**Table 4.** Article classification (Webster and Watson, 2002).

| Article | Combination of methods? | Type of simulation | Application examples? | Industry |
|---|---|---|---|---|
| Yan, 2016 | No | Probability model | Yes | Other |
| Konstantin et al., 2014 | Yes (ML) | Decision model | Yes | Energy industry |
| Aksyonov et al., 2013 | Yes (ML) | Decision model | Yes | Energy industry |
| Bruzzone et al., 2009 | Yes (SM and others) | Probability model | Yes | Food industry |
| Stahmer and Schwaiger, 2004 | Yes (others) | Decision & Probability model | Yes | Food industry |
| Munoz, 2003 | No | Probability model | No | General |

## 4. Analysis of research

The following analysis deals with the research questions. The first question "How many publications deal with simulation as a sales forecasting method?" can be answered by the results of the SLR. 152 articles could be categorized as relevant to the topic of simulation as a method for forecasting. However, it should be emphasized that although these touch the topic, not all articles use simulation to carry out sales forecasting. Some of the articles use simulation only as a complementary method to the actual sales forecast, as can be seen in Section 3.3 by the publication from Sakai et al. (1994). Another example is Kaczmarek and Hryniewicz (2013), in which the existing sales forecast is improved with the help of synthetic data generated in Monte Carlo simulation.

To answer the second research question, Figure 2 clearly shows how the number of publications in the study area has increased over time and, therefore, that a further increase can be expected.

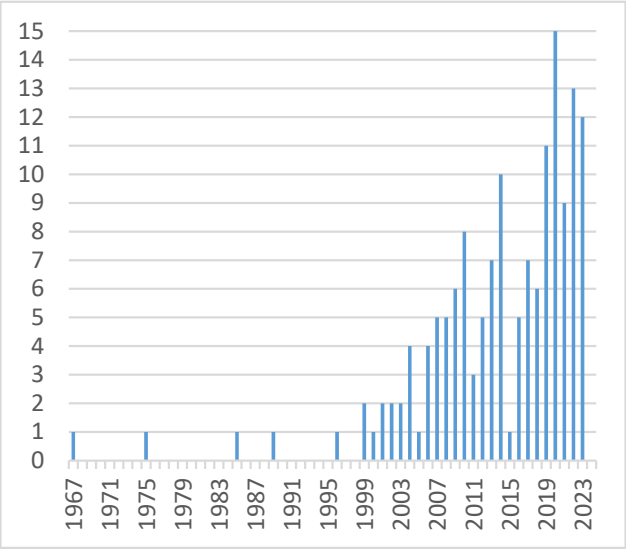


**Figure 2.** Number of publications per year.

When considering simulation as an application-oriented method, it becomes clear that almost all publications contain an application example (127 of 152).

The next question to be answered is whether simulation is combined with other methods. All publications were analyzed to determine whether and, if so, which methods were combined. A distinction was made between ML, SM, the combination of several simulation methods, and all methods that did not fit into the first three categories (listed under "Other"). "Other" includes methods such as expert estimates, results of empirical studies on customer psychology or linguistic knowledge concepts. Figure 3 shows that simulation was used in combination with other methods in more than half of the publications. SM is most frequently combined with simulation due to its ease of application. This is followed by ML. Here, the high accuracy potential of the forecasting method is used exclusively, and simulation is only used for support (in almost all cases for data generation).

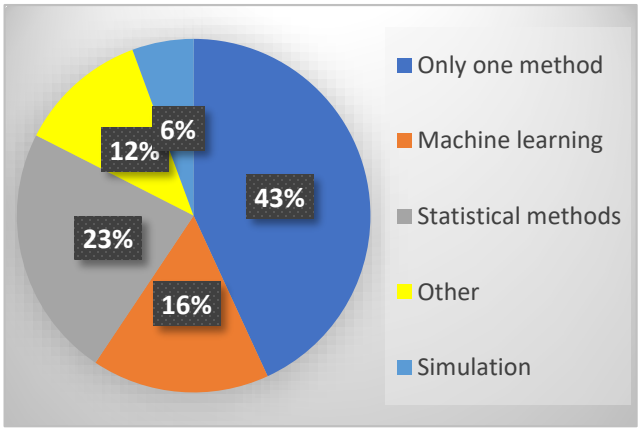


**Figure 3.** Combination of methods.

When looking at the different simulation methods used, most of them could be assigned (17 are not mentioned). The remaining 135 articles were sorted into the categories listed in Section 3.3. In total, there are 148 categorizations made, as several were used in some articles. The result can be found in Figure 4. Decision models are most strongly represented. They are closely followed by probability models. These two were, therefore, analyzed in more detail. In the case of the decision models, the models that were explained in more detail were mostly agent-based models (ABMs) (45 of 65). 91 % of these were used for simulating customer behavior and the resulting sales and 42 % were combined with other methods. In one third of all ABMs, the prediction of customer behavior was combined with other forecasting methods in order to improve it. The MCS was usually used for probability models (42 %). This simulation was often used with other methods to test the actual sales forecast by generating synthetic data or to increase their accuracy. MCS and ABM together account for 43 % of all methods

used.

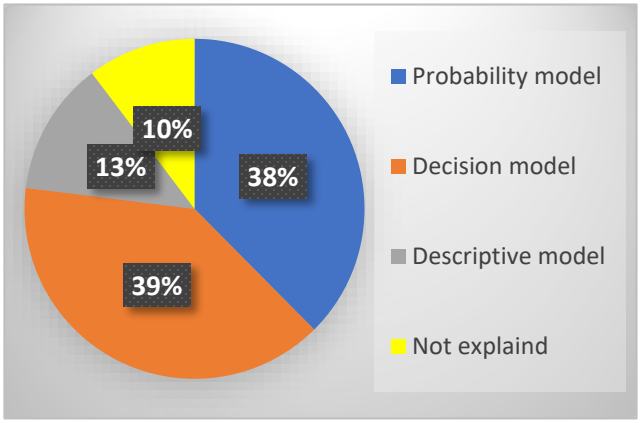


**Figure 4.** Types of simulation methods used.

When categorizing the publications under review by industry, it becomes evident that four sectors are strongly represented. One of these sectors is the automotive industry, where many (sales) forecasts relate to the future direction of the electric car. In the second sector, the food industry, most publications relate to food retailing with a shopping basket tailored to customer behavior. The third is the energy sector. The picture for the energy sector is not quite as clear. There are some more recent publications relating to renewable energies or the sale of electricity in general, but also a similar number of publications on sales forecasts at petrol stations. Entertainment electronics and telecommunications are prevalent in the electronics industry (fourth sector). In telecommunications in particular, great importance is attached to predicting the behavior of new and existing customers.

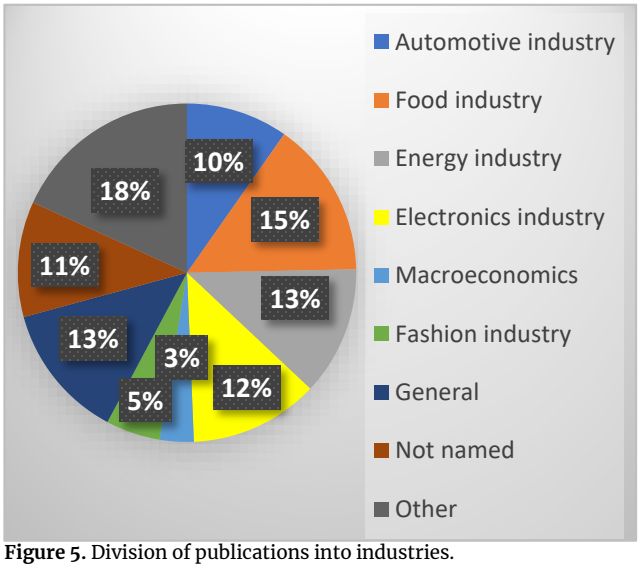


**Figure 5.** Division of publications into industries.

It has already been found in this section that almost all publications have an application focus and more than half of them combine two or more methods. This shows that the answer to the last research question is relevant for both research and practice. Looking at the 57 % combined methods, it can be seen that simulation was used in most cases as a supplement to another forecasting method. This addition is divided into two large areas. On the one hand, simulation is used to generate randomized sales data. On the other hand, simulation is applied to analyze more complex cause-effect relationships, where an attempt is made to gain a deeper understanding. This deeper understanding is often aimed at analyzing a specific behavior (customer, market, product, employee, etc.). An example of the first area is Engle et al. (1989), where a simulation was carried out to assess the effectiveness of various forecasting techniques for the electricity market. Thirty-eight years of data were generated. The first 28 were used to train the models, and the last ten years of 120 months were forecast based only on the data from the first 28 years. In another publication, which deals with the Australian subsidiary of a Japanese automotive company, not all the data were generated synthetically, but the existing data were supplemented by synthetic data due to a lack of data, in order to improve the forecasts through exponential smoothing (Snyder, 2002).

The approach proposed in Bruzzone et al. (2009) fits well with the second area. It is based on the combination of simulation, time series analysis, and data fusion to produce forecasts that can support the human resource organization. The model receives data from the supermarket network; the time series data on sales, labor hours, customers, and material flows are processed and the forecasts are subjected to data fusion and combined with the simulation of workloads. The model provides forecasts for the total operational load for planning activities in supermarkets. In addition, the proposed approach enables the estimation of future values for targets such as sales and productivity and the comparison of historical data to support forward-looking resource and policy management. Here, the simulation model is used for optimization and varies depending on the user's prioritization. A simulation model for the supermarket is also created by Schwenke et al. (2012). In addition to the avoidance of remaining stock, the forecasting of sales of special offers is also considered. In practice, the sales of regular products can be predicted by applying time series analysis or simply by the experience of the store managers. However, the causal relationships between the observed objects, namely the supermarket and the customers, remain unexplored. Especially for the investigation of the more irregular behavior of offered special promotions, simulation at a lower level of individual objects (customers, products, shopping trolleys, sales receipts) should achieve greater accuracy and offer the possibility to change these circumstances.

To answer the last research question, the latest publications were prioritized in order to identify the current research gap. Table 5 shows all publications from the year 2023.

**Table 5.** All articles from 2023 (Webster and Watson, 2002).

| Article | Combination of methods? | Type of simulation | Application examples? | Industry |
|---|---|---|---|---|
| Baloian et al., 2023 | Yes (ML) | Not mentioned | Yes | Food industry |
| Dasilva et al., 2023 | Yes (SM) | Probability model | Yes | Food industry |
| Huang et al., 2023 | No | Decision model | No | Automot industry |
| Khlyupina et al., 2023 | No | Descriptive model | Yes | Food industry |
| Marc and Berlec, 2023 | No | Probability model | Yes | Other |
| Ramírez-Velíz et al., 2023 | No | Probability model | Yes | Food industry |
| Schlaich and Hoberg, 2023 | No | Not mentioned | Yes | Food industry |
| Sundararaman and Ramalingam, 2023 | Yes (others) | Decision model | Yes | Fashion industry |
| Svetunkov and Boylan, 2023 | No | Descriptive model | Yes | Food industry |
| Wei et al., 2023 | No | Probability model | Yes | Automotive industry |
| Yan and Hu, 2023 | Yes (other) | Decision model | Yes | General |
| Zeng et al., 2023 | Yes (other) | Decision model | Yes | Not mentioned |

These articles were selected on the basis of their topicality. The research gaps and suggestions for improvement indicated that they were categorized into different areas in Figure 6. Publications that openly point out a general gap were sorted under "General gap". Publications that only point out suggestions for transfer to other areas, the weaknesses of one's own work or suggestions for improvement were categorized under "Specific gap". A good example of this category is Khlyupina et al. (2023). There are minor comments for the improvement of one's own model, but the whole thing is very specific to the used case. Publications that do not state anything have been categorized under "No gap", which includes Ramírez-Velíz et al. (2023).

None of the 12 publications describes a general research gap. The publications that address the need for further research always describe which improvements should be made for their own specific model. They usually deal with improving or adding certain parameters.

When analyzing all publications classified as relevant, it should be noted that no generally applicable procedure could be described. The model is always designed and further developed for a specific area (industry, sales channel, type of model or application).

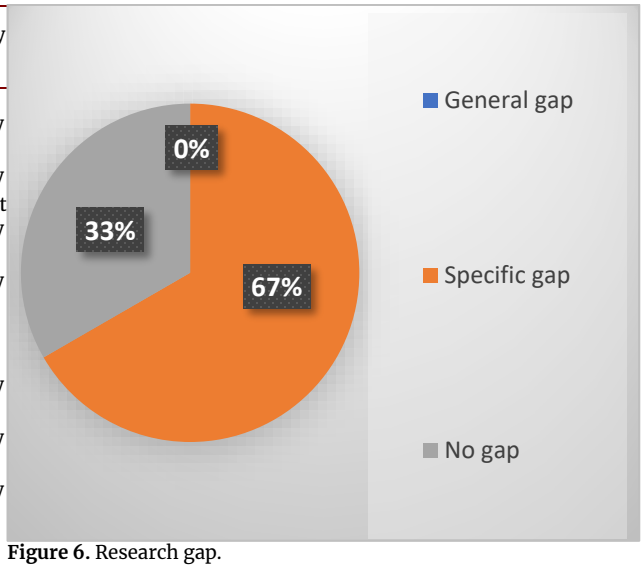


**Figure 6.** Research gap.

## 5. Conclusions

The goal of this systematic literature review was to provide a comprehensive overview on the application of simulation as a method for sales forecasting, following the approach of Webster and Watson (2002), Cato (2016), and Von Brocke et al. (2009). The scope of the study was defined and research questions were set up to analyze how simulation can be utilized to create or enhance sales forecasts and how widespread the use of this method currently is. Next, the search parameters were defined and the databases were selected. The search yielded 532 articles and after filtering out the irrelevant ones and a forward and backward search, 152 relevant articles were considered. These articles were categorized in a table (examples are shown in Table 3). The sorting was based on which areas are covered in the respective article and how intensively. It was also taken into account whether the areas in these articles were mutually linked or treated separately from each other. After this categorization, the research questions for each article were answered individually. An example is shown in Table 4. This was followed by the actual analysis part in which these answers were combined to form an overall picture.

When looking at the results, although 152 articles were identified as relevant for the study, only some of them used simulation directly as a method for sales forecasting, and often in combination with other methods. The other papers only used it as support for the actual forecasting method. The results shed light on the trend in this area of research. Figure 2 shows that the number of publications per year has significantly increased over time, indicating a growing interest in this topic. By analyzing the various simulation methods used, a variety of approaches was identified. Decision and probability models make up a significant portion. It is evident that there is a rich diversity of simulation

methods employed in different contexts.

Looking at all 152 articles by industries, food, energy, electronics, and automotive were the most prevalent ones, with food retailing, renewable energies and oil, telecommunication, and electric vehicles taking the lead in their respective areas. The systematic literature review shows an increasing interest and activity in the area of simulation as a sales forecasting method, but not as the sole method. Rather, simulation has been used as a complementary method to statistical methods or machine learning as the main sales forecasting method. The increasing number of publications and the diverse application examples signal the potential for further research and development in this area. Future endeavors dealing with simulation-based sales forecasting will probably focus on decision models or probability models and investigate possible synergies with machine learning or statistical methods.

When looking at the research gap in the latest publications, it becomes clear that they only point out the need for further action for a very specific model or problem. This again demonstrates the importance of this review due to its broader perspective, because it becomes clear that, in addition to improving individual parameters of the specific simulation model, extended cross-sector solutions are also interesting. This could also start on a small scale with cross-divisional or cross-channel solutions. This can be an important starting point for future studies. Another starting point would be to create a structured procedural model for the creation of simulation models for sales forecasts. This should definitely take into account the additional use of other methods.

Another further starting point for future studies is the review itself. Although this offers a large quantitative coverage, it cannot carry out a qualitative assessment of the effective benefit of the methods used due to its size. This would be necessary in order to weight the relevant publications differently. For the qualitative evaluation, one could first concentrate on individual sectors and make recommendations for their application. The most strongly represented sectors would be suitable here.

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